Practical Data Science using R Lesson 4: Visualizing Data with `ggplot`

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About the lesson

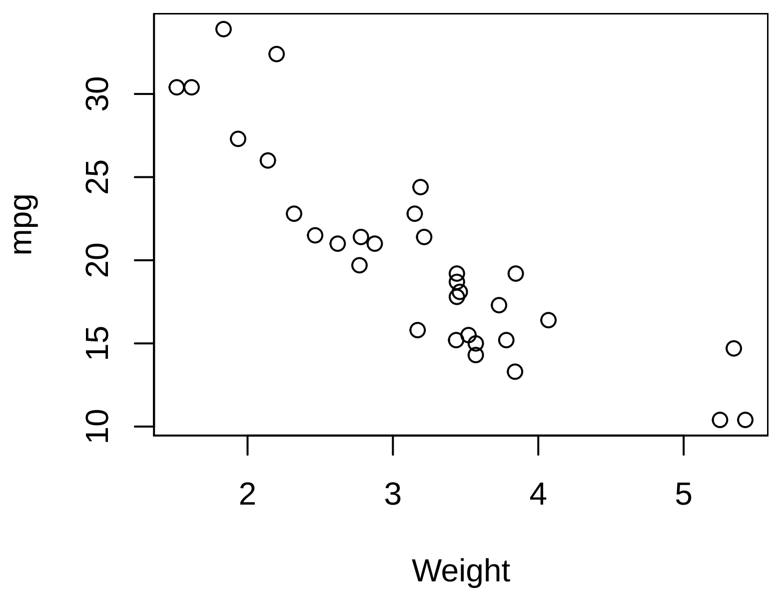
- Visualizing data is the core activity of the exploratory analysis phase
- In this lesson, we learn how to produce plots using the `ggplot2` package
- The focus of the lesson is on scatterplots, barplots, boxplots, and histograms
- We'll also learn how to improve the readability of the plot by using facets

Plotting with Base R

Base R has basic plotting functions that suffice for basic tasks

Example, generating scatterplots with `plot` is straight forward:

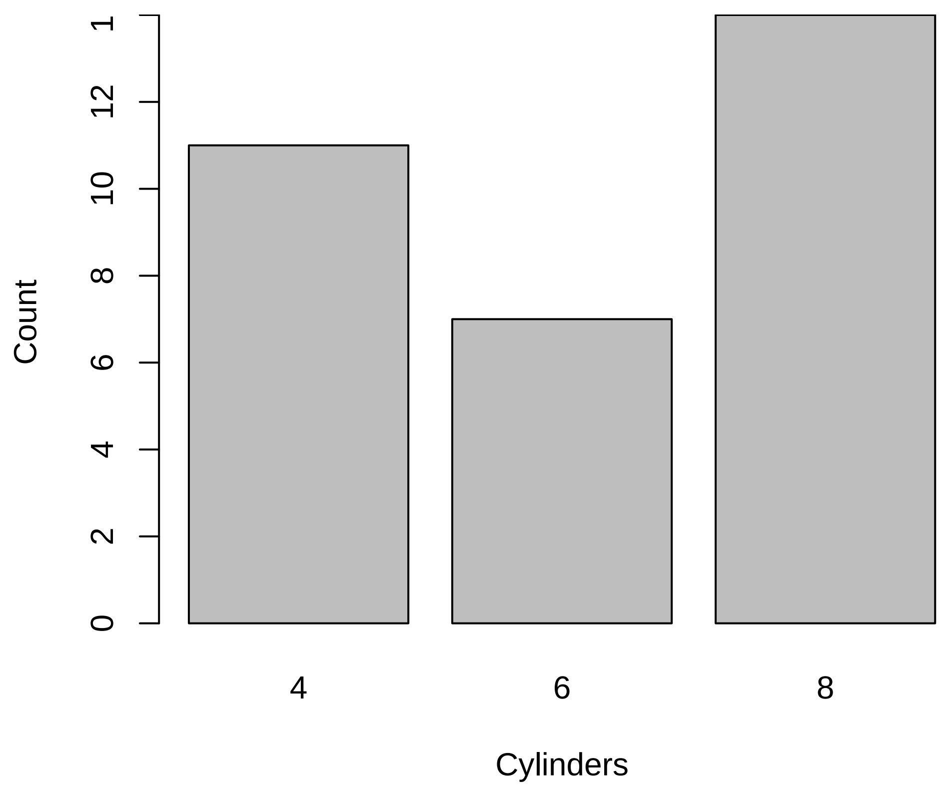
```
data(mtcars)
par(mar=c(4,4,0,0))
plot(mtcars$wt, mtcars$mpg, xlab="Weight", ylab="mpg")
```



Plotting with Base R

So is generating barplots with `barplot`:

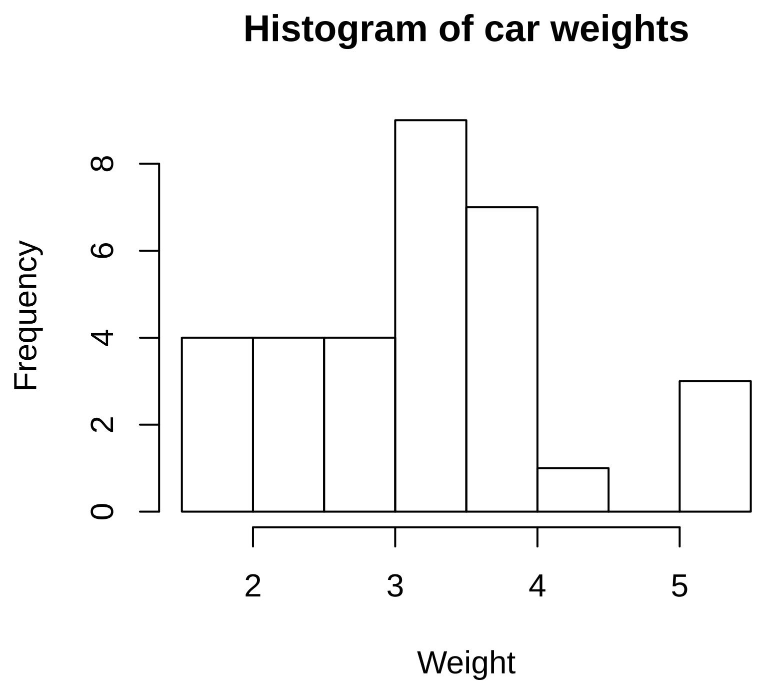
```
par(mar=c(4,4,0,0))
barplot(table(mtcars$cyl), xlab="Cylinders", ylab="Count")
```



Plotting with Base R

Histograms with `hist`:

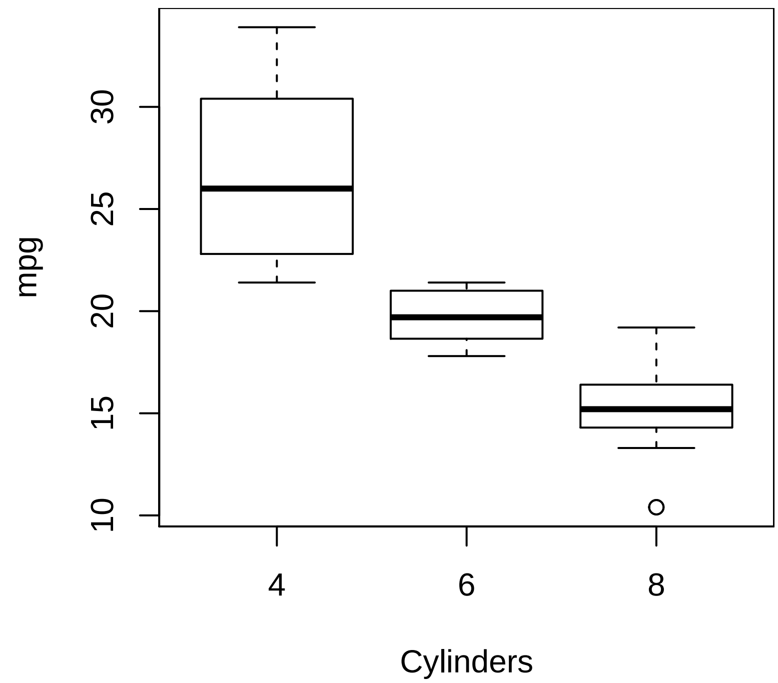
```
par(mar=c(4,4,4,0))
hist(mtcars$wt, xlab="Weight", main="Histogram of car weights")
```



Plotting with Base R

And boxplots with `boxplot`:

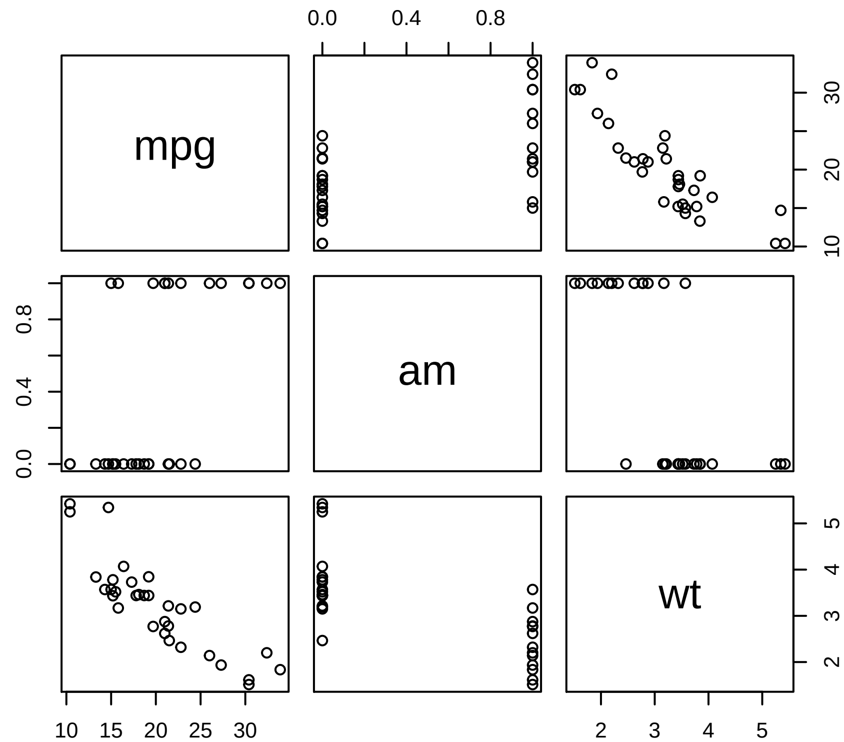
```
par(mar=c(4,4,0,0))
boxplot(mtcars$mpg ~ mtcars$cyl, xlab="Cylinders", ylab="mpg")
```



Plotting with Base R

`pairs` is a quick way for visualizing pairwise comparisons:

```
pairs(mtcars[,c("mpg", "am", "wt")])
```



Motivation for using `ggplot`

- Nicer looking plots (publication quality)
- Uses a layered approach to plotting (easy to add elements to existing plots)
- Allows showing multiple plots through faceting
- Integrates statistical analysis within the same package
- Works with **tidy data**
- Is an implementation of **The Grammar of Graphics** (a well founded approach to plotting data in quantitative fields)

The Grammar of Graphics

There are seven elements to a plot:

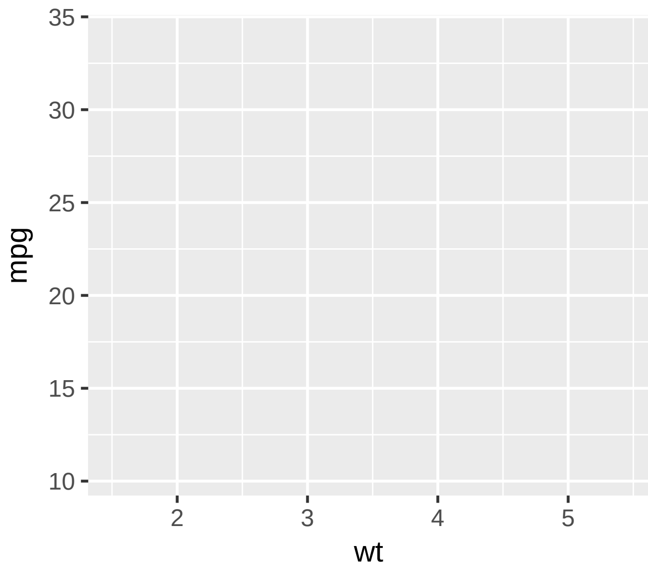
- **Data**: The dataset being plotted
- **Aesthetics**: The scale onto which we map the data

- **Geometries**: The visual elements used for the data
- **Statistics**: The data analysis performed on the plotted data
- **Coordinates**: The dimensions of the plot
- **Facets**: The splitting of a single plot into multiple plots
- **Themes**: Visual elements that are not part of the data

ggplot Scatterplots

The ggplot function deals with the data and aesthetics elements:

```
library(ggplot2)
ggplot(data = mtcars, aes(x = wt, y = mpg))
```

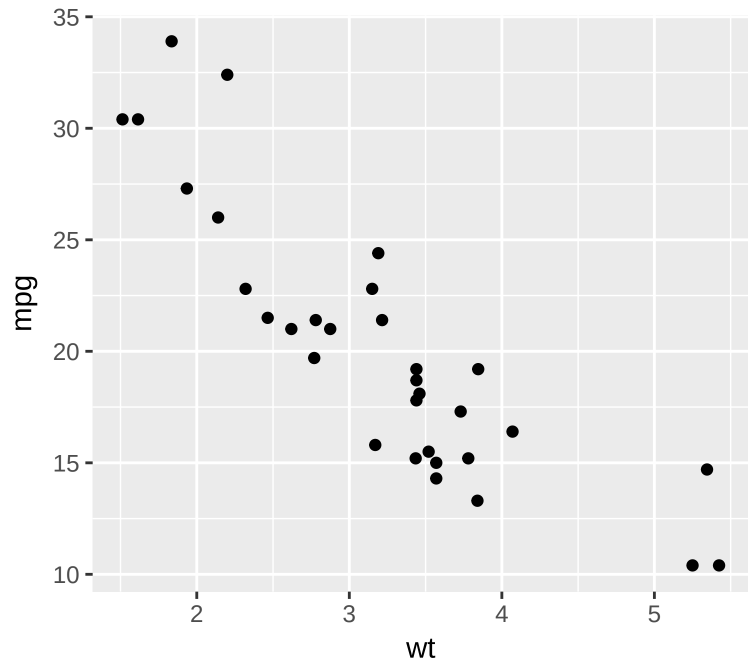


The plot is empty! We need to define the geometrical element

ggplot Scatterplots

We specify a scatterplot by the geom_point function:

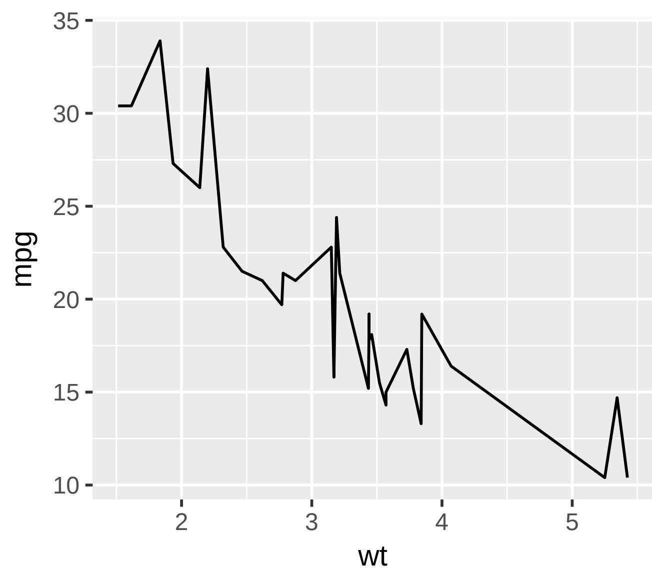
```
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_point()
```



`ggplot` Scatterplots

We could've made this a line plot instead by using the `geom_line` function:

```
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_line()
```

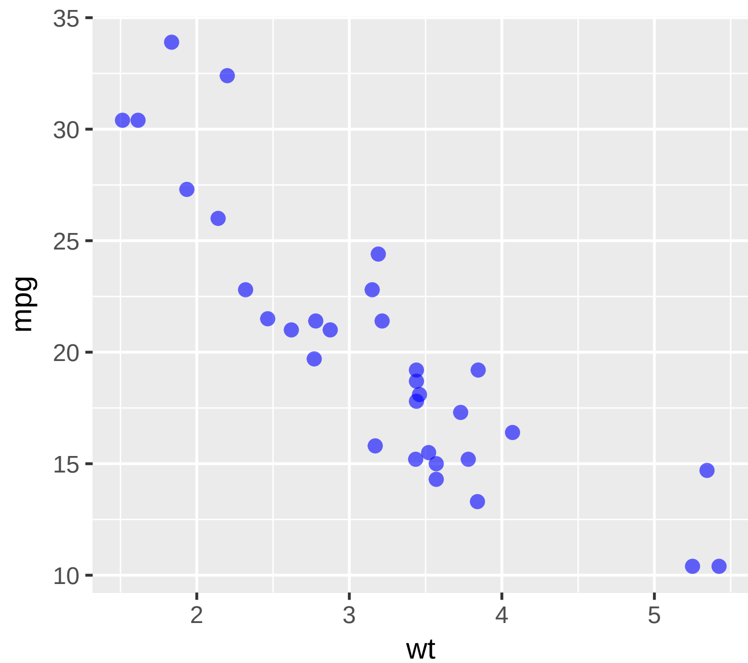


But that doesn't make sense for the plotted data

`ggplot` Scatterplots

We control the properties of the data points within `geom_point`:

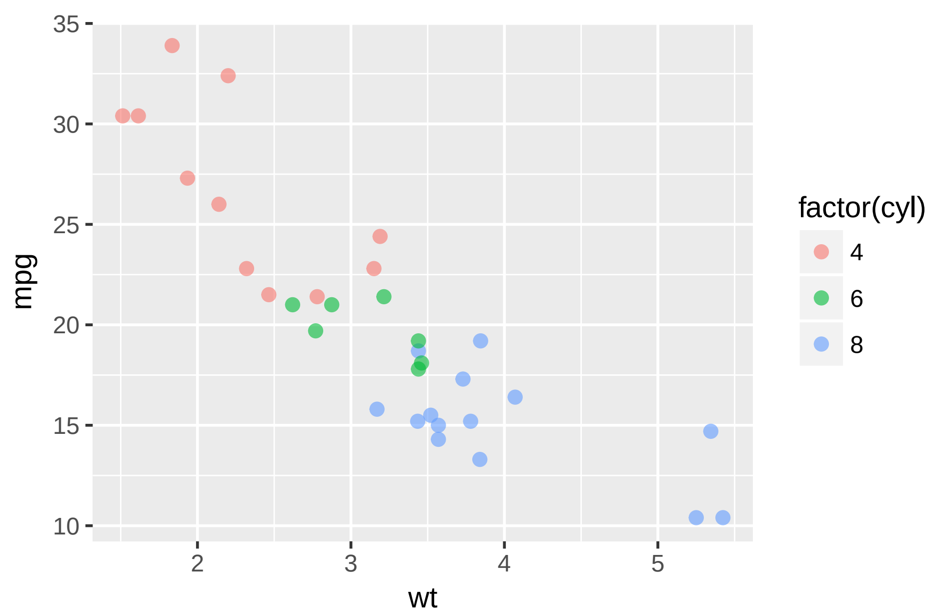
```r
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_point(size = 2, col = "blue", alpha = 0.6)
```



ggplot Scatterplots

We can add other dimensions to the plot within `aes`:

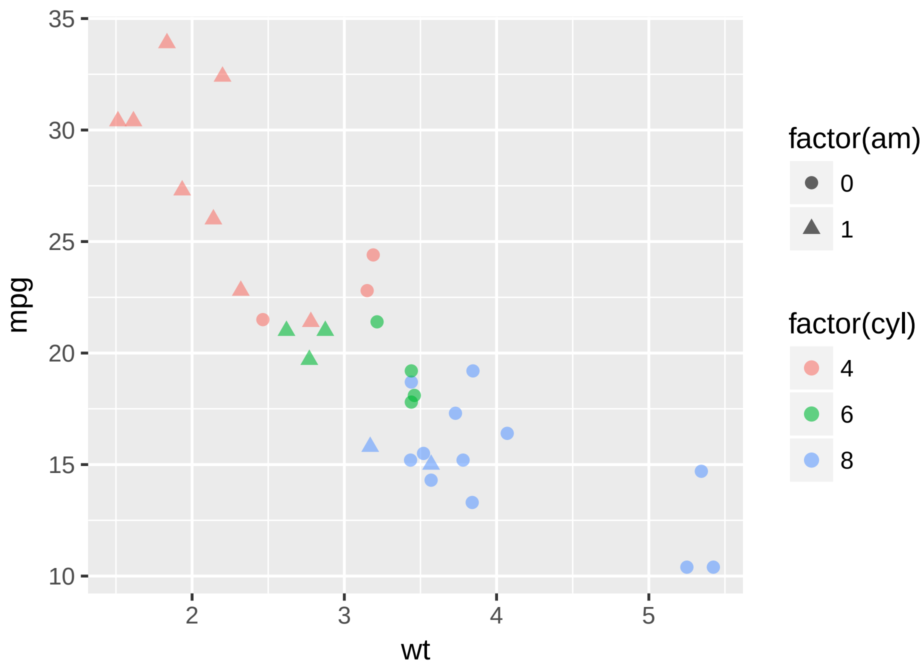
```r
ggplot(data = mtcars, aes(x = wt, y = mpg, col = factor(cyl))) +
  geom_point(size = 2, alpha = 0.6)
```



The number of cylinders are mapped to the color

ggplot Scatterplots

```r
ggplot(data = mtcars, aes(x = wt, y = mpg,
    col = factor(cyl), shape = factor(am))) +
    geom_point(size = 2, alpha = 0.6)
```



And the transmission type is mapped to the shape

Now is your turn to practice!

The iris dataset is a record of petal and sepal dimensions for three different species of the iris flower. The dataset can be loaded in R by calling:

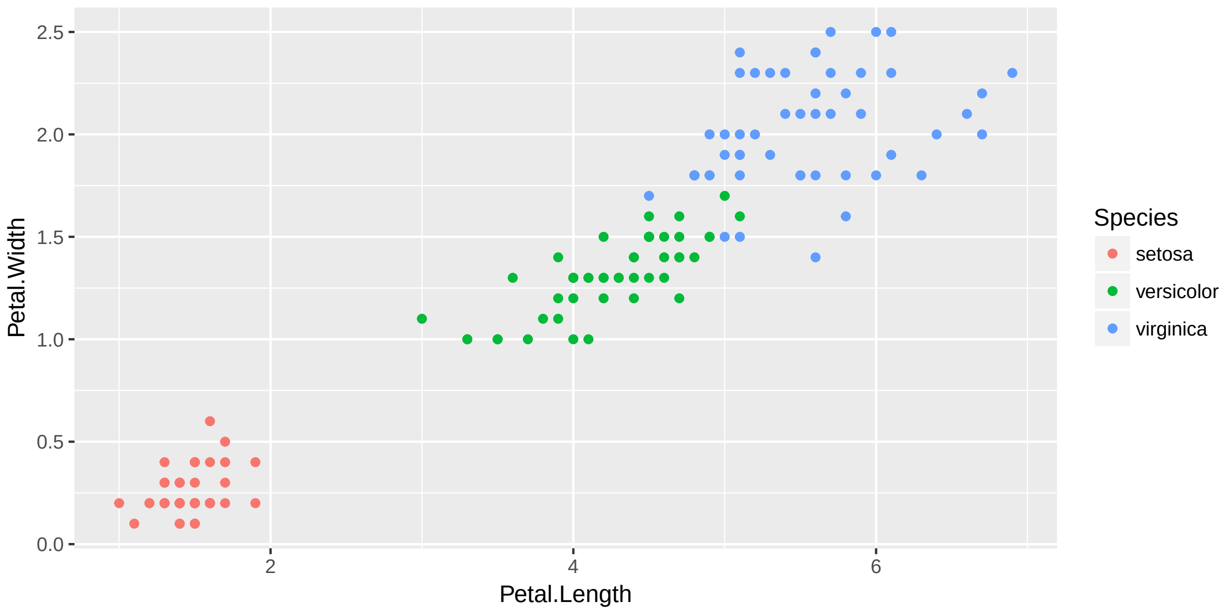
```r
data(iris)
```

Use `ggplot` to generate a scatterplot of petal width vs. petal length with the color of the data point indicating the iris species.

Iris Petal Length and Width

Here's a possible solution to the previous exercise:

```r
ggplot(iris, aes(x= Petal.Length, y = Petal.Width, col = Species )) +
  geom_point()
```



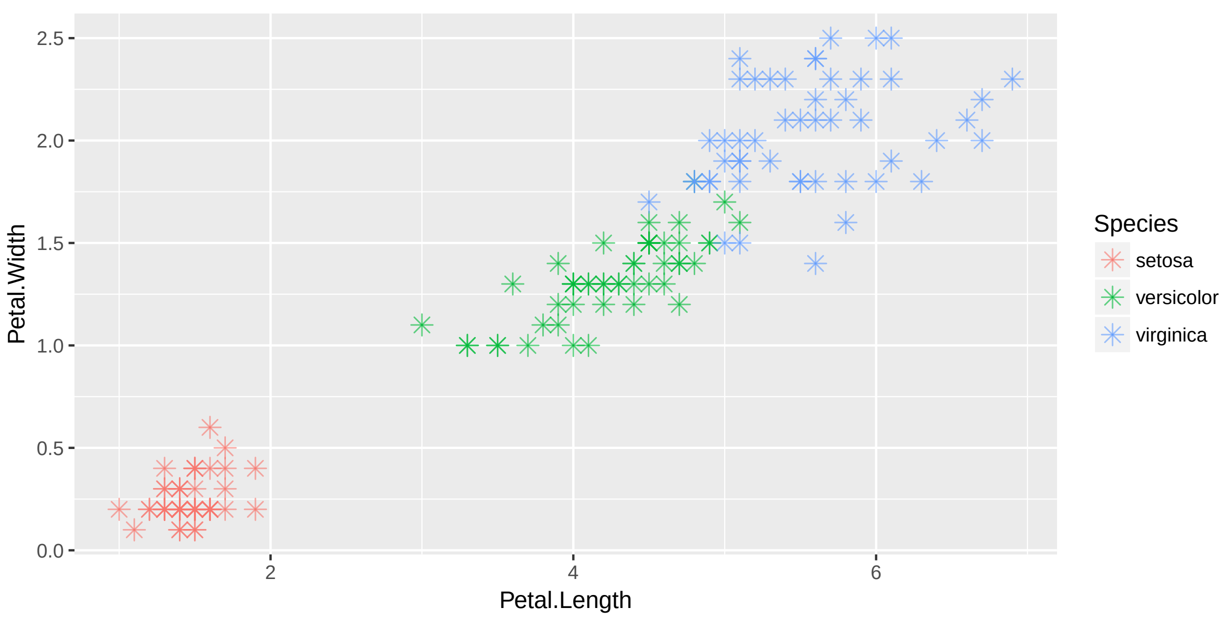
Now is your turn to practice!

Update the scatterplot of petal width vs. petal length by changing the size, transparency, and shape of the data points.

Iris Petal Length and Width

Here's a possible solution to the previous exercise:

```
ggplot(iris, aes(x= Petal.Length, y = Petal.Width, col = Species )) +
  geom_point(size=3, alpha=0.6, shape=8)
```

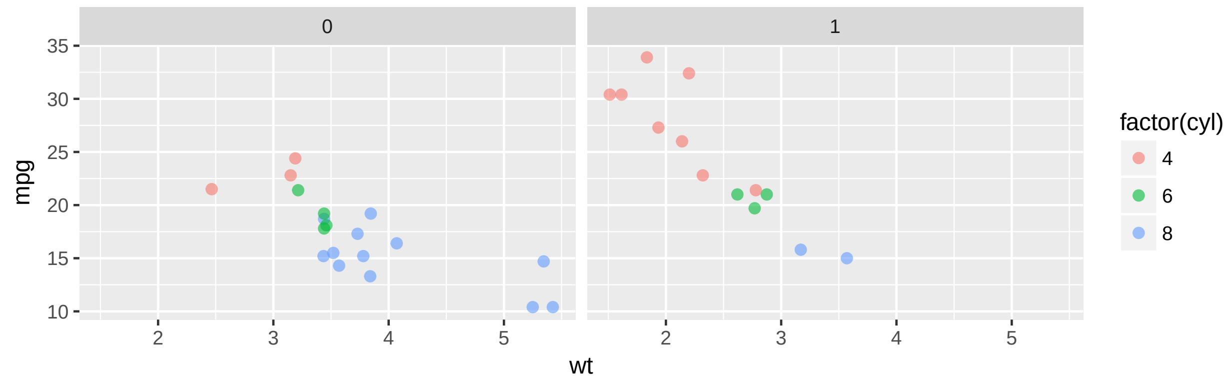


Faceted plots

Faceted plots is a way to split a 'busy' looking plot into multiple plots for better readability

This is done with `facet_wrap`:

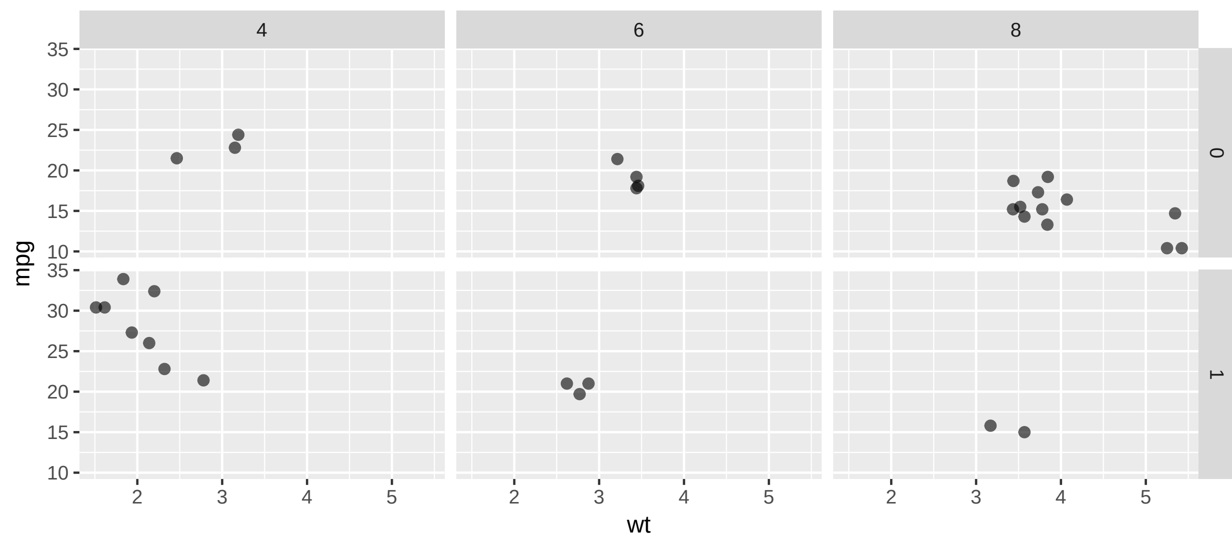
```
ggplot(data = mtcars, aes(x = wt, y = mpg, col = factor(cyl)) ) +
  geom_point(size = 2, alpha = 0.6) +
  facet_wrap(~am)
```



Faceted plots

`facet_grid` allows faceting by two variables:

```
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_point(size = 2, alpha = 0.6) +
  facet_grid(am~cyl)
```



Dataframe format

To map a variable onto a ggplot aesthetic or facet, the variable has to be in a proper tidy format

Example, here's another look at the iris dataset:

```r
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

The format of the dataset allows faceting by Species, but not by part (e.g. Petal vs. Sepal)

Now is your turn to practice!

Generate a facet plot that shows sepal and petal dimensions in separate panels. Each panel is a scatterplot of width vs. length, with the color of the data point indicating iris species.

As the `iris` dataset as loaded directly from R is not in the proper format to do the required analysis, I created this alternative tidy version:

`https://raw.githubusercontent.com/maherharb/MATE-T580/master/Datasets/iris_alt.csv`

```
## # A tibble: 4 x 5
##   Species    Id  Part Length Width
##     <chr> <int> <chr>  <dbl> <dbl>
## 1  setosa     1 Petal    1.4   0.2
## 2  setosa     1 Sepal    5.1   3.5
## 3  setosa     2 Petal    1.4   0.2
## 4  setosa     2 Sepal    4.9   3.0
```

Iris Petal Length and Width

Let’s take a look at the iris dataset:

```r
head(iris)
```

```
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
## 1          5.1         3.5          1.4         0.2  setosa
## 2          4.9         3.0          1.4         0.2  setosa
## 3          4.7         3.2          1.3         0.2  setosa
## 4          4.6         3.1          1.5         0.2  setosa
## 5          5.0         3.6          1.4         0.2  setosa
## 6          5.4         3.9          1.7         0.4  setosa
```

Sepal and Petal dimensions need not be in separate columns. We need to do some work with `gather` and `spread`

Iris Petal Length and Width

First, we combine all variables:

```r
library(dplyr)
library(tidyr)
iris2 <- iris %>%
  mutate(Id = 1:n()) %>%
```

```r
  gather(Measure, Value, Sepal.Length:Petal.Width)
head(iris2)
```

```
##   Species Id      Measure Value
## 1  setosa  1 Sepal.Length   5.1
## 2  setosa  2 Sepal.Length   4.9
## 3  setosa  3 Sepal.Length   4.7
## 4  setosa  4 Sepal.Length   4.6
## 5  setosa  5 Sepal.Length   5.0
## 6  setosa  6 Sepal.Length   5.4
```

Iris Petal Length and Width

Then we separate the Part (Sepal vs. Petal) from the Dimension (Length vs. Width):

```r
iris3 <- separate(iris2, Measure, c("Part", "Dimension"), "[.]")
head(iris3)
```

```
##   Species Id  Part Dimension Value
## 1  setosa  1 Sepal    Length   5.1
## 2  setosa  2 Sepal    Length   4.9
## 3  setosa  3 Sepal    Length   4.7
## 4  setosa  4 Sepal    Length   4.6
## 5  setosa  5 Sepal    Length   5.0
## 6  setosa  6 Sepal    Length   5.4
```

Iris Petal Length and Width

And finally, we spread the Dimension into separate Width and Length columns:

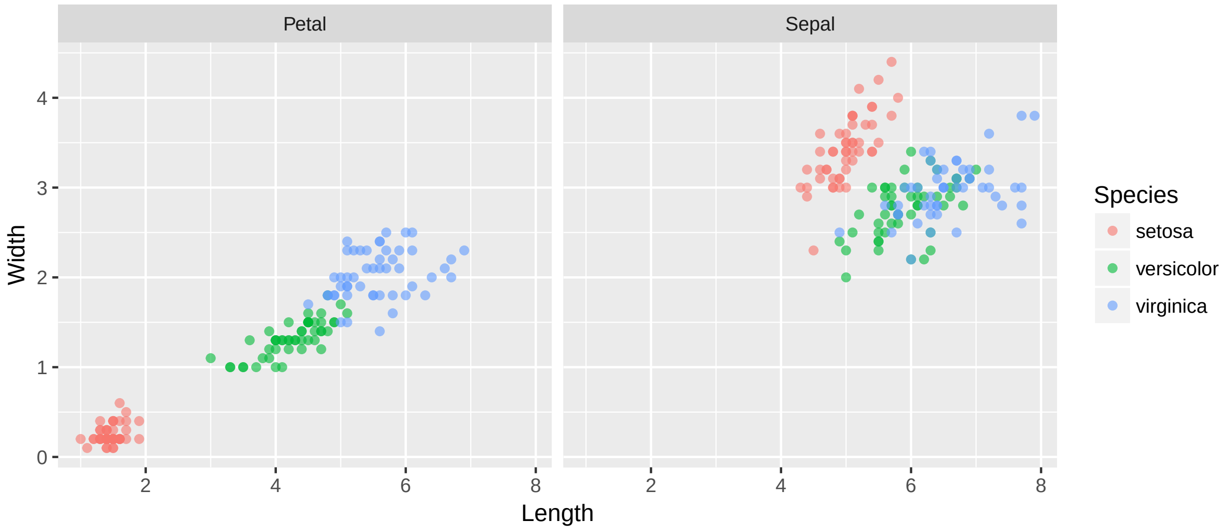
```r
iris4 <- spread(iris3, Dimension, Value)
head(iris4)
```

```
##   Species Id  Part Length Width
## 1  setosa  1 Petal    1.4   0.2
## 2  setosa  1 Sepal    5.1   3.5
## 3  setosa  2 Petal    1.4   0.2
## 4  setosa  2 Sepal    4.9   3.0
## 5  setosa  3 Petal    1.3   0.2
## 6  setosa  3 Sepal    4.7   3.2
```

Iris Petal Length and Width

Here's a possible solution to the previous exercise:

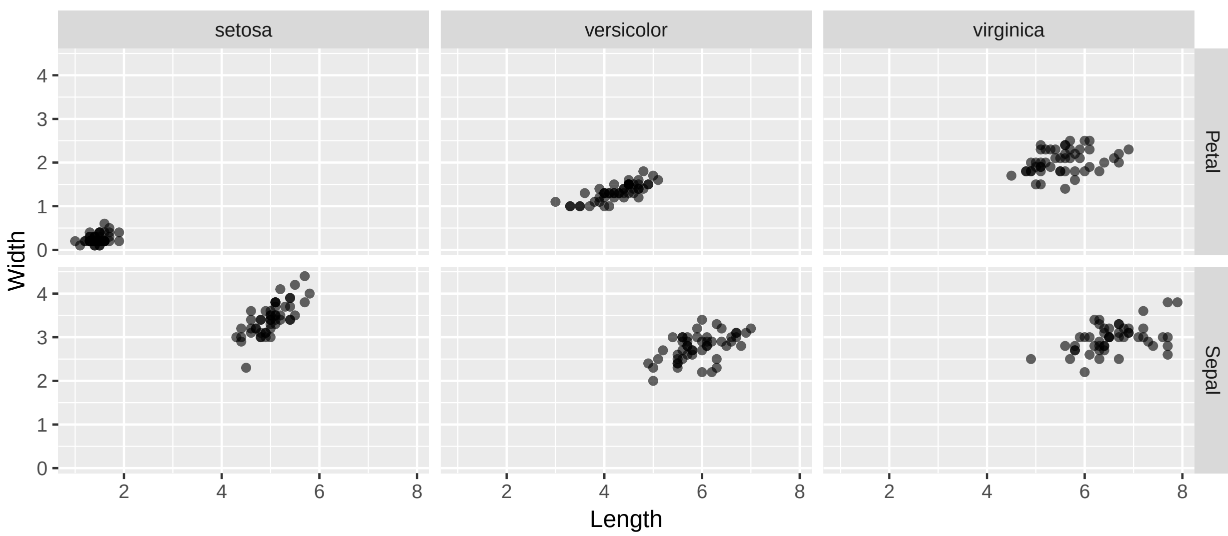
```r
 ggplot(iris4, aes(x= Length, y = Width, col = Species )) +
   geom_point(alpha=0.6) +
  facet_wrap(~Part)
```



Iris Petal Length and Width

Here's another way to visualize the data:

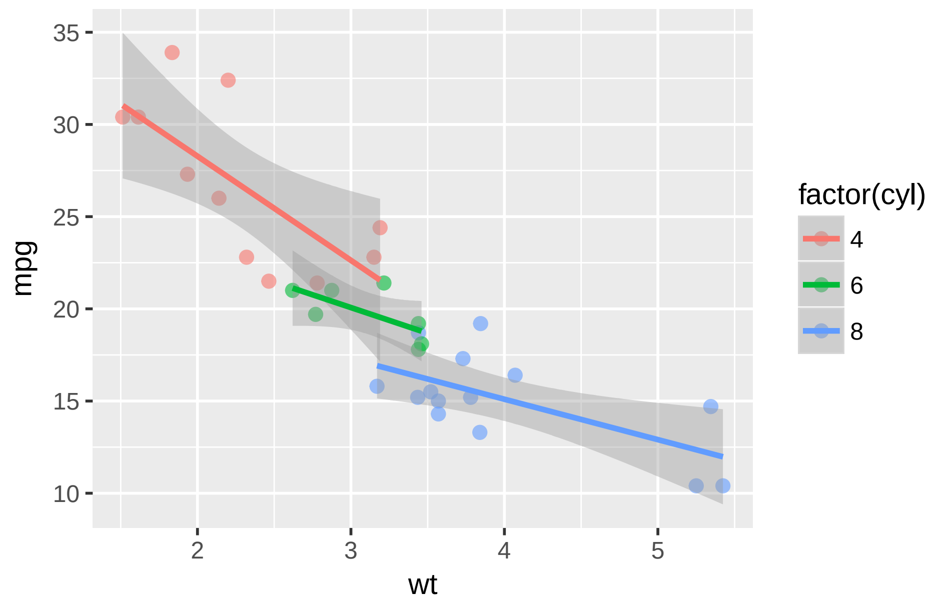
```
ggplot(iris4, aes(x= Length, y = Width )) +
  geom_point(alpha=0.6) +
 facet_grid(Part~Species)
```



Adding statistical elements to plots

In `ggplot`, statistical analysis is treated like a separate element that can be added to plots:

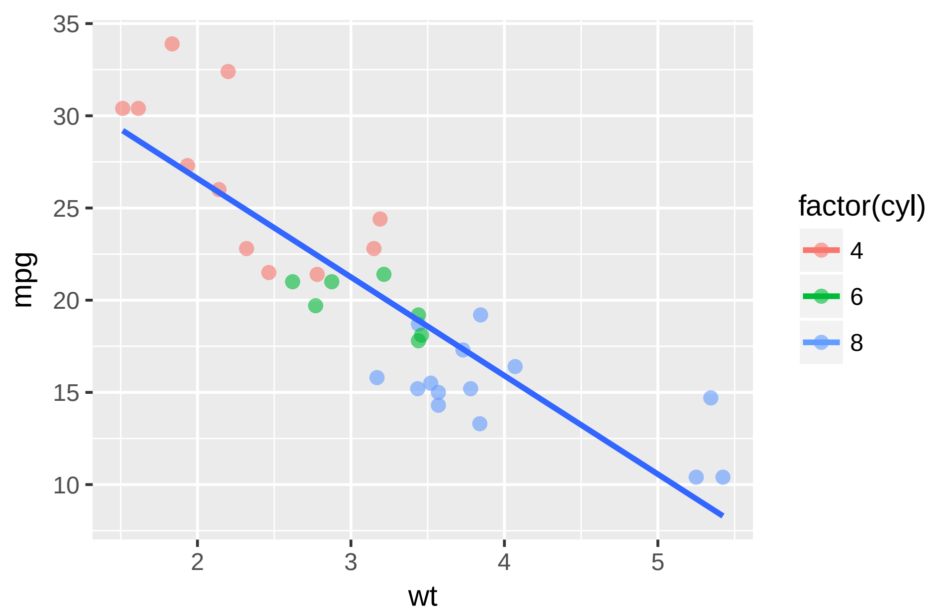
```
ggplot(data = mtcars, aes(x = wt, y = mpg, col = factor(cyl))) +
  geom_point(size = 2, alpha = 0.6) +
  stat_smooth(method="lm")
```



Adding statistical elements to plots

Alternatively, we can perform the fit on the entire data:

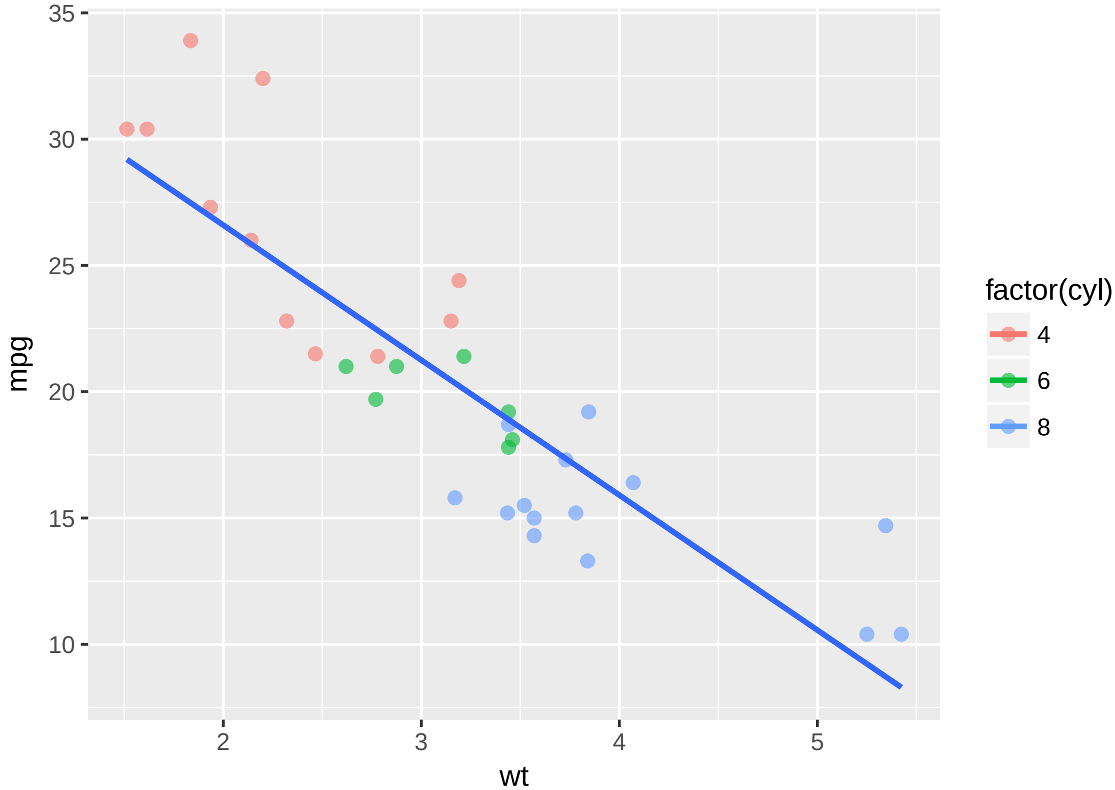
```
ggplot(data = mtcars, aes(x = wt, y = mpg, col = factor(cyl))) +
  geom_point(size = 2, alpha = 0.6) +
  stat_smooth(aes(group = 1), method="lm", se=FALSE)
```



Flash-forward

In lesson 6, we'll learn how the line of best fit is generated

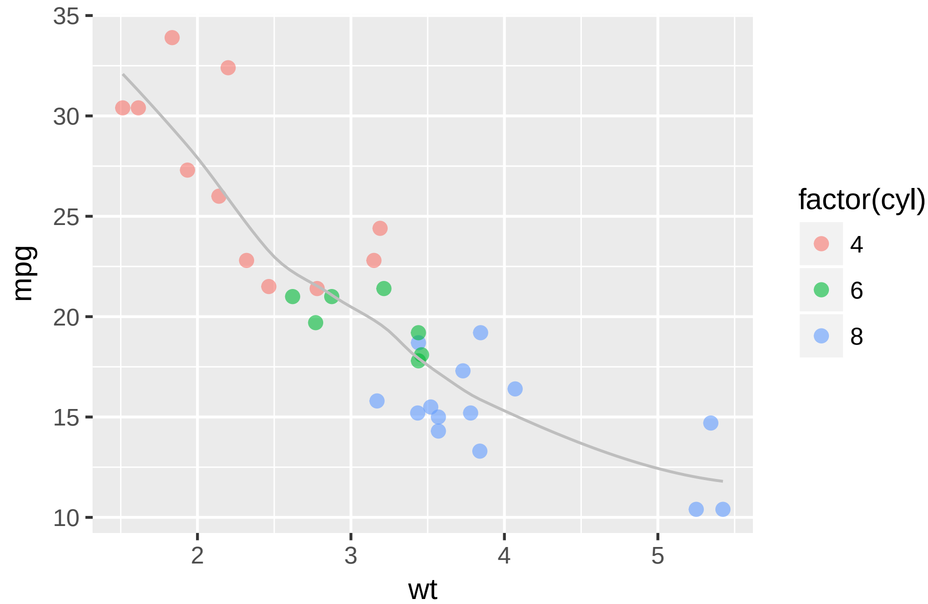
```r
ggplot(data = mtcars, aes(x = wt, y = mpg, col = factor(cyl))) +
  geom_point(size = 2, alpha = 0.6) +
  stat_smooth(aes(group = 1), method="lm", se=FALSE)
```



Adding statistical elements to plots

We can also add trend lines with `stat_smooth`:

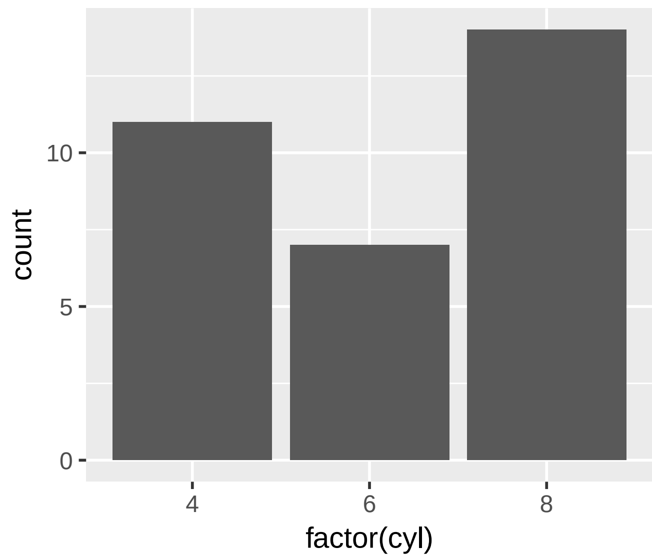
```r
ggplot(data = mtcars, aes(x = wt, y = mpg, col = factor(cyl))) +
  geom_point(size = 2, alpha = 0.6) +
  stat_smooth(aes(group = 1), se=FALSE, lwd=0.5, col="gray")
```



ggplot Barplots

The very basic purpose of a barplot is to count:

```
ggplot(data = mtcars, aes(x = factor(cyl))) +
  geom_bar()
```

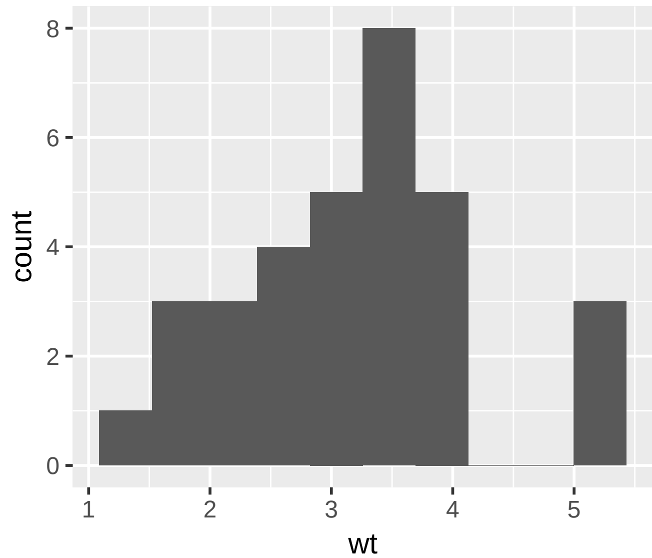


Notice that cylinder is a categorical variable

ggplot Histograms

If the x variable is numeric, we use `geom_histogram` instead:

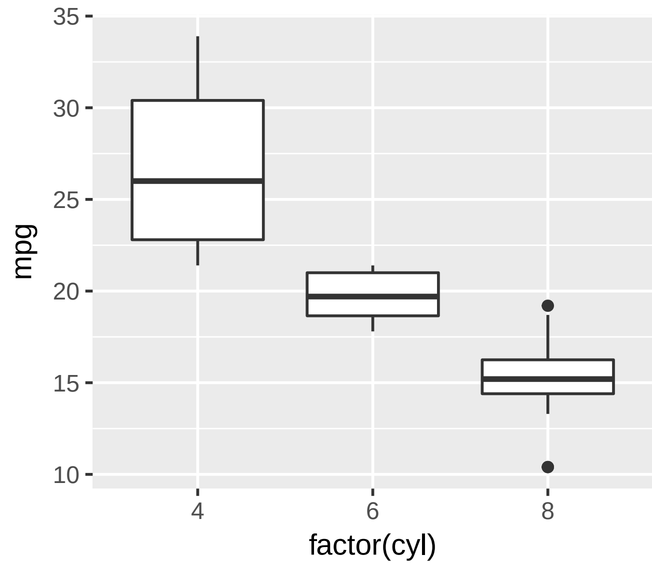
```r
ggplot(data = mtcars, aes(x = wt)) +
  geom_histogram(bins=10)
```



ggplot Boxplots

Displaying statistics of a numerical variable against a categorical variable is done with `geom_boxplot`:

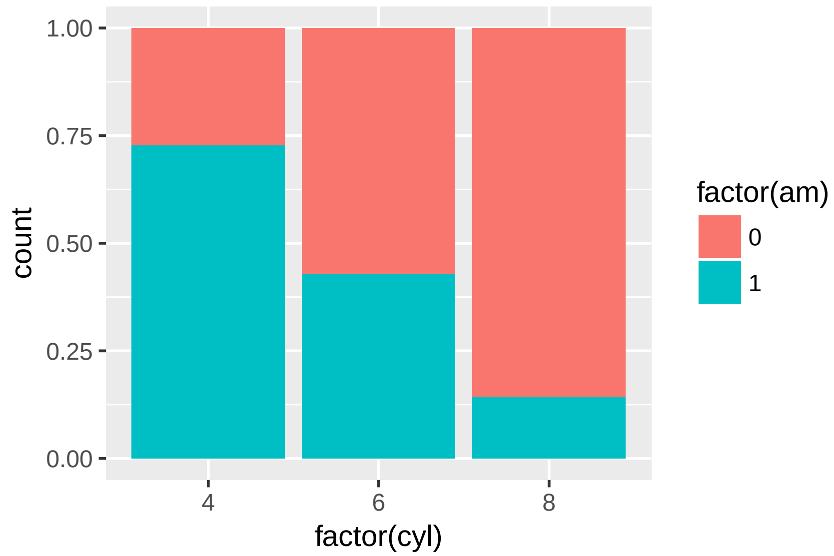
```r
ggplot(data = mtcars, aes(x = factor(cyl), y=mpg)) +
  geom_boxplot()
```



ggplot Barplots

We can use `geom_bar` for multivariate plots:

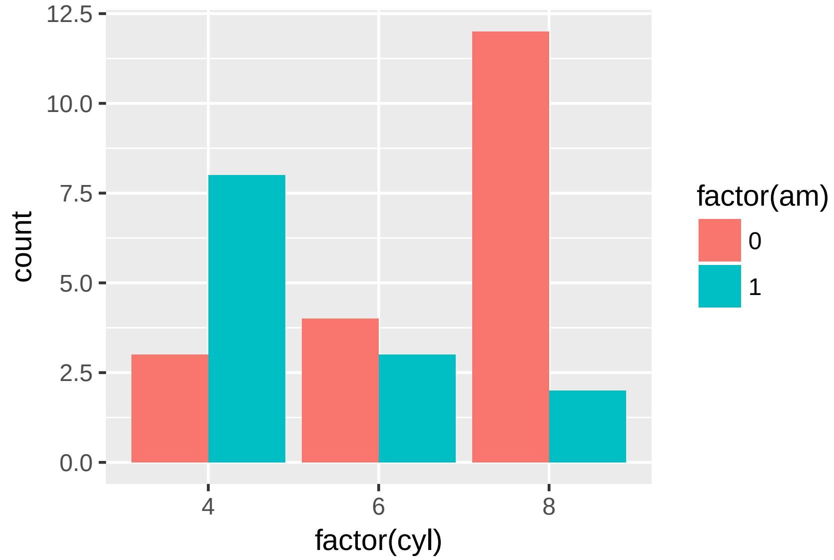
```r
ggplot(data = mtcars, aes(x = factor(cyl), fill=factor(am))) +
  geom_bar(position="fill")
```



ggplot Barplots

An alternative way to display the same data:

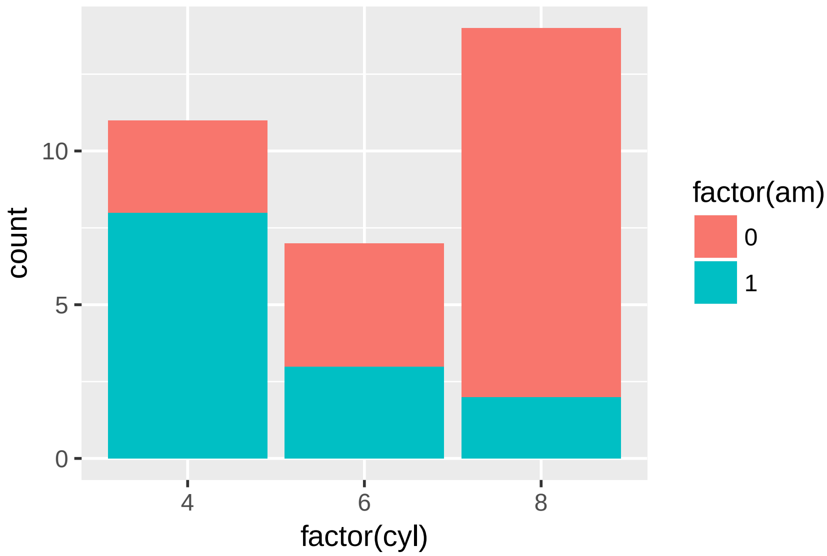
```r
ggplot(data = mtcars, aes(x = factor(cyl), fill=factor(am))) +
  geom_bar(position = "dodge")
```



ggplot Barplots

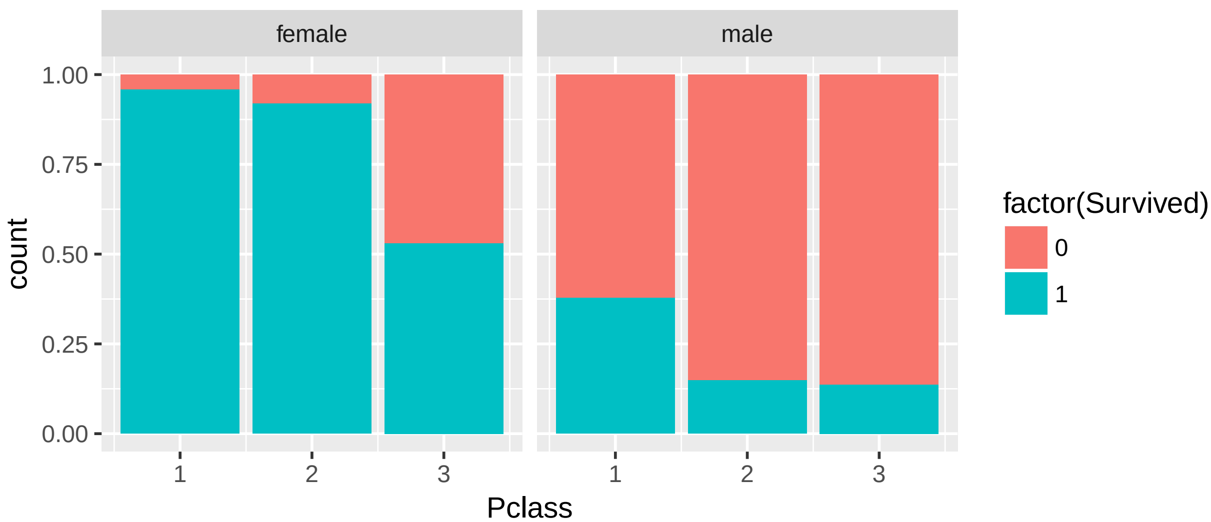
An alternative way to display the same data:

```r
ggplot(data = mtcars, aes(x = factor(cyl), fill=factor(am))) +
  geom_bar(position = "stack")
```



Now is your turn to practice!

Here's a barplot showing survival rates for the titanic passengers, by class and gender:



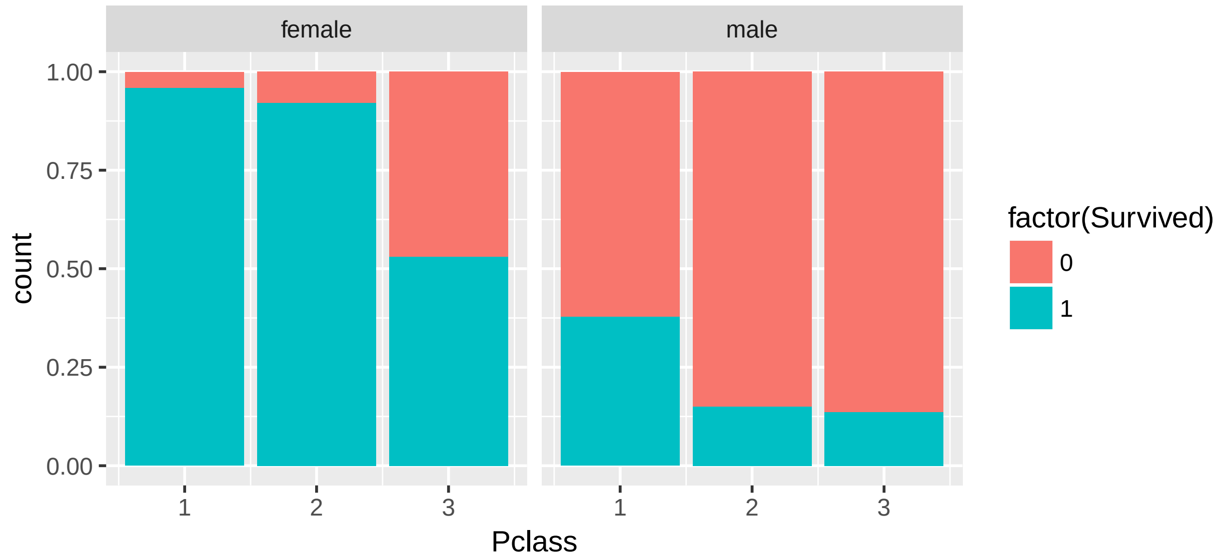
Your task is to reproduce the same plot. Link to the titanic dataset:

https://raw.githubusercontent.com/maherharb/MATE-T580/master/Datasets/titanic_train.csv

Titanic survival by class, gender

Here's the code that generated the previous plot:

```r
df_titanic %>% ggplot(aes(x = Pclass, fill = factor(Survived)) +
    geom_bar(position = "fill") + facet_wrap(~Sex)
```

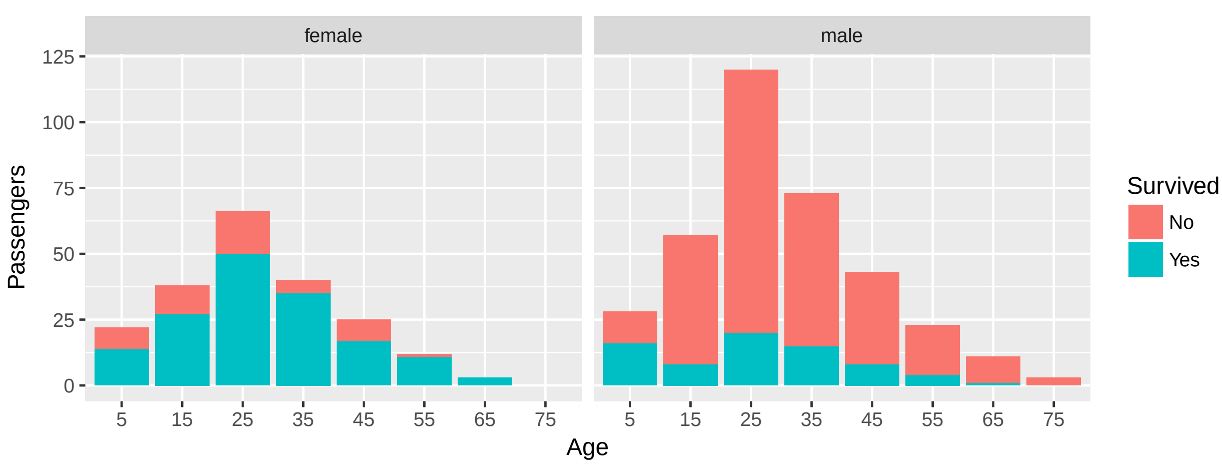


Now is your turn to practice!

Using the same titanic data, make a plot with `ggplot` that explores the relationship between survival, age, and gender. This's an open ended exercise, you may generate any type of plot you wish as long as it effectively communicates the relationship of interest.

Titanic survival by age, gender

```
df_titanic %>% filter(!is.na(Age), !is.na(Survived),
    !is.na(Sex)) %>% mutate(Age_group = cut(Age,
    breaks = c(seq(0, 90, 10), Inf), labels = seq(5,
        95, 10))) %>% mutate(Survived = factor(ifelse(Survived,
    "Yes", "No"))) %>% ggplot(aes(x = Age_group,
    fill = Survived)) + geom_bar(position = "stack") +
    facet_wrap(~Sex) + xlab("Age") + ylab("Passengers")
```



Now is your turn to practice!

Let's work with the Nobel prizes dataset found here:

`https://raw.githubusercontent.com/maherharb/MATE-T580/master/Datasets/Nobel_data_full.csv`

Generate a visualization that ranks countries by total number of prizes, and at the same time shows breakdown of prizes by prize category

Nobel prizes

Start by selecting the relevant columns and rows:

```
df_nobel <- read_csv("Nobel_data_full.csv") %>%
    select(Year, Category, Country1 = `Organization Country`,
        Country2 = `Birth Country`)

df_nobel$Country1[is.na(df_nobel$Country1)] <- df_nobel$Country2[is.na(df_nobel$Country1)]
df_nobel <- na.omit(df_nobel)
dim(df_nobel)
```

```
## [1] 943   4
```

```
head(df_nobel)
```

```
## # A tibble: 6 x 4
##    Year   Category    Country1           Country2
##   <int>      <chr>       <chr>              <chr>
## 1  1901  Chemistry     Germany        Netherlands
## 2  1901 Literature      France             France
## 3  1901   Medicine     Germany   Prussia (Poland)
## 4  1901      Peace Switzerland        Switzerland
## 5  1901      Peace      France             France
## 6  1901    Physics     Germany Prussia (Germany)
```

Nobel prizes

Then do a bit of cleaning to the country names:

```
library("stringr")
df_nobel <- df_nobel %>% mutate(Country1 = str_replace(Country1,
    "Federal Republic of Germany", "Germany")) %>%
    mutate(Country1 = str_replace(Country1,
        "Union of Soviet Socialist Republics",
        "Russia")) %>% mutate(Country1 = str_replace(Country1,
    "Alsace.+", "France")) %>% group_by(Country1) %>%
    mutate(Total = n()) %>% ungroup() %>%
    filter(Total > 2)
head(df_nobel)
```

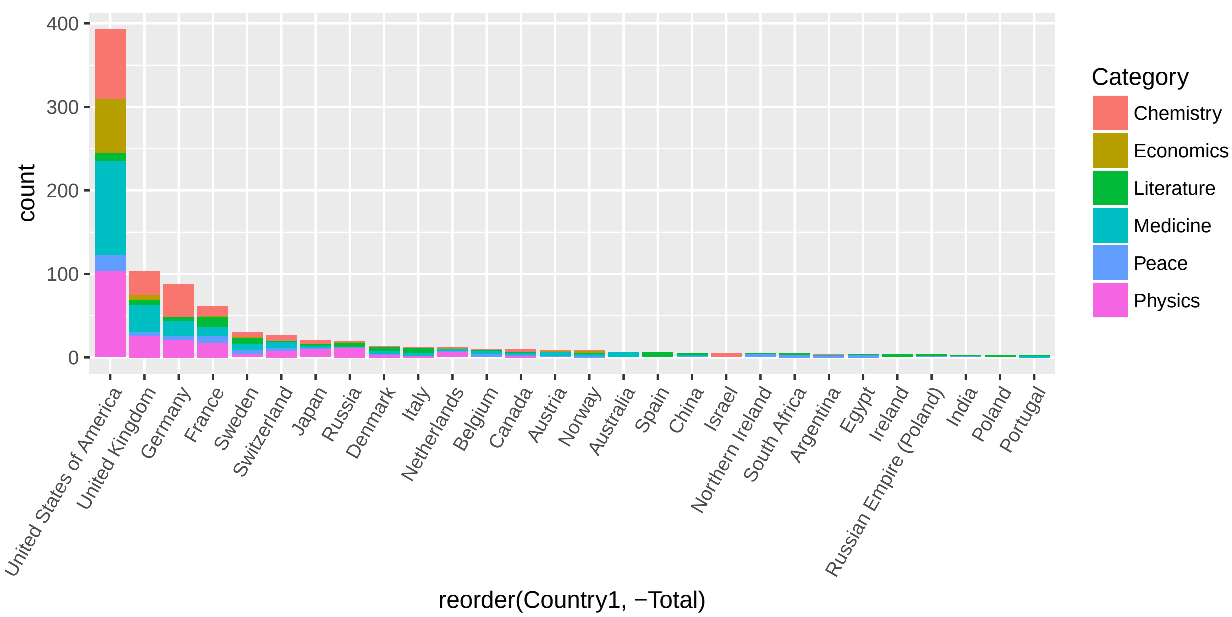
```
## # A tibble: 6 x 5
##    Year   Category    Country1           Country2 Total
##   <int>      <chr>       <chr>              <chr> <int>
## 1  1901  Chemistry     Germany        Netherlands    88
## 2  1901 Literature      France             France    61
```

```
## 3  1901   Medicine     Germany  Prussia (Poland)    88
## 4  1901      Peace Switzerland        Switzerland    26
## 5  1901      Peace      France            France    61
## 6  1901    Physics     Germany Prussia (Germany)    88
```

Nobel prizes

Then make a bar plot with ggplot:

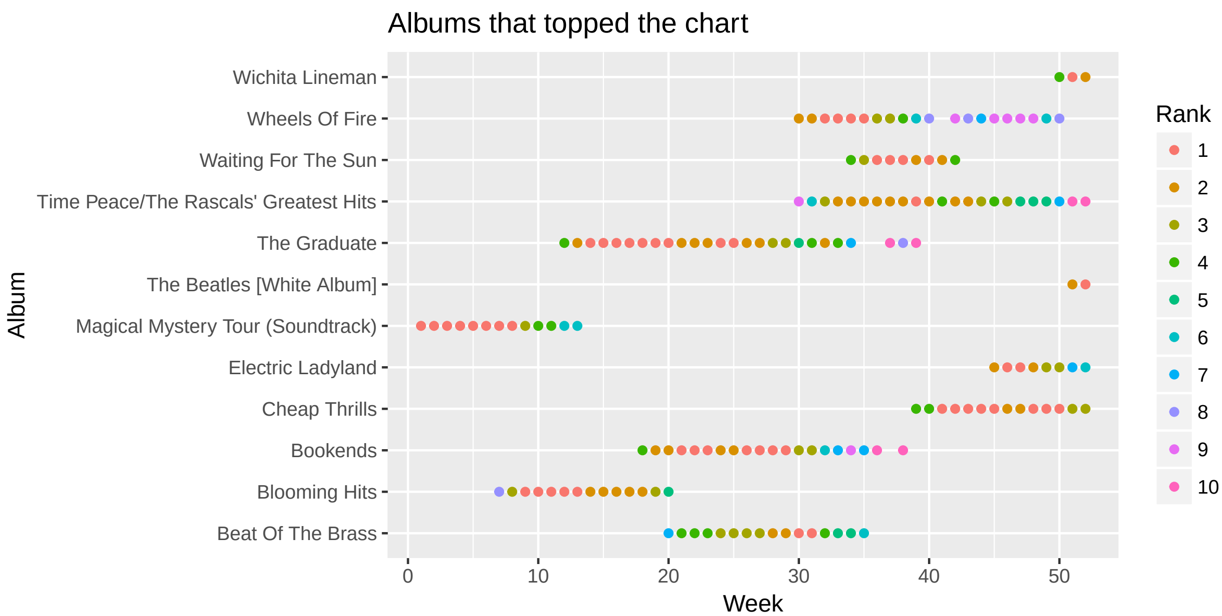
```
df_nobel %>% ggplot(aes(x = reorder(Country1, -Total), fill = Category)) + geom_bar(position = "stack")
    theme(axis.text.x = element_text(angle = 60, hjust = 1))
```



Billboard Top 10 Albums

With ggplot we can create some nonintuitive mappings:

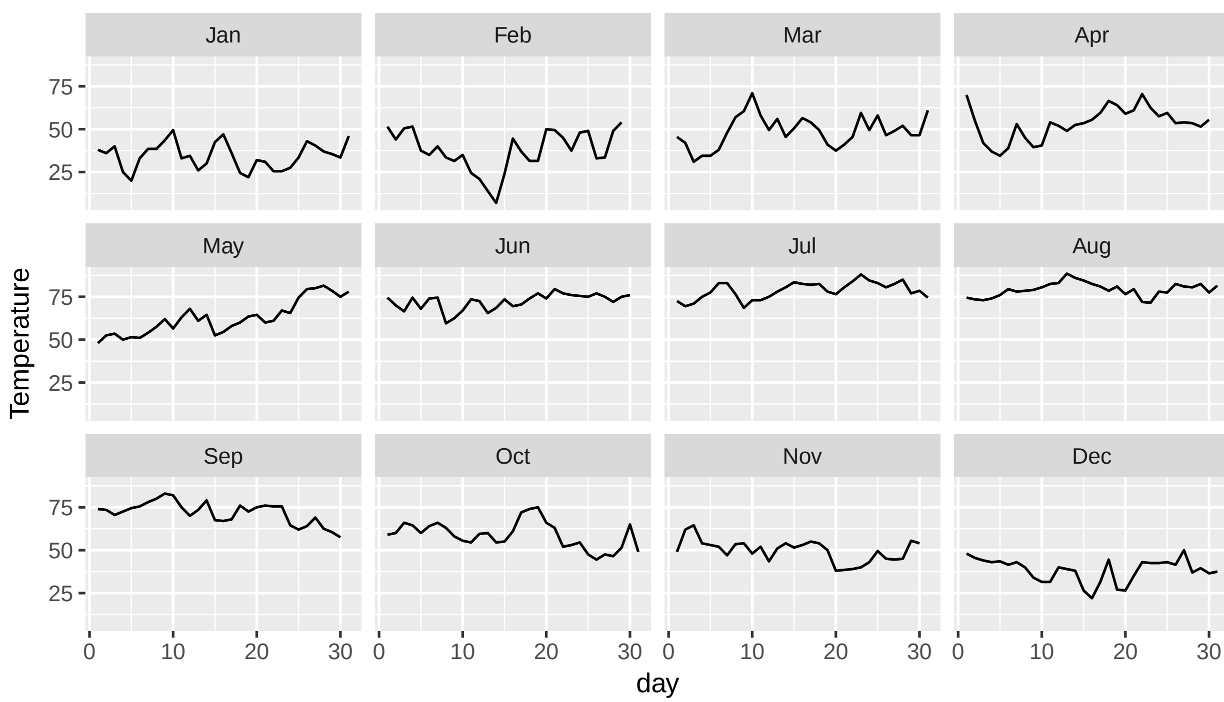
```
ggplot(df_billboard3, aes(x = Week, y = Album,
    col = Rank)) + geom_point() + labs(titles = "Albums that topped the chart")
```



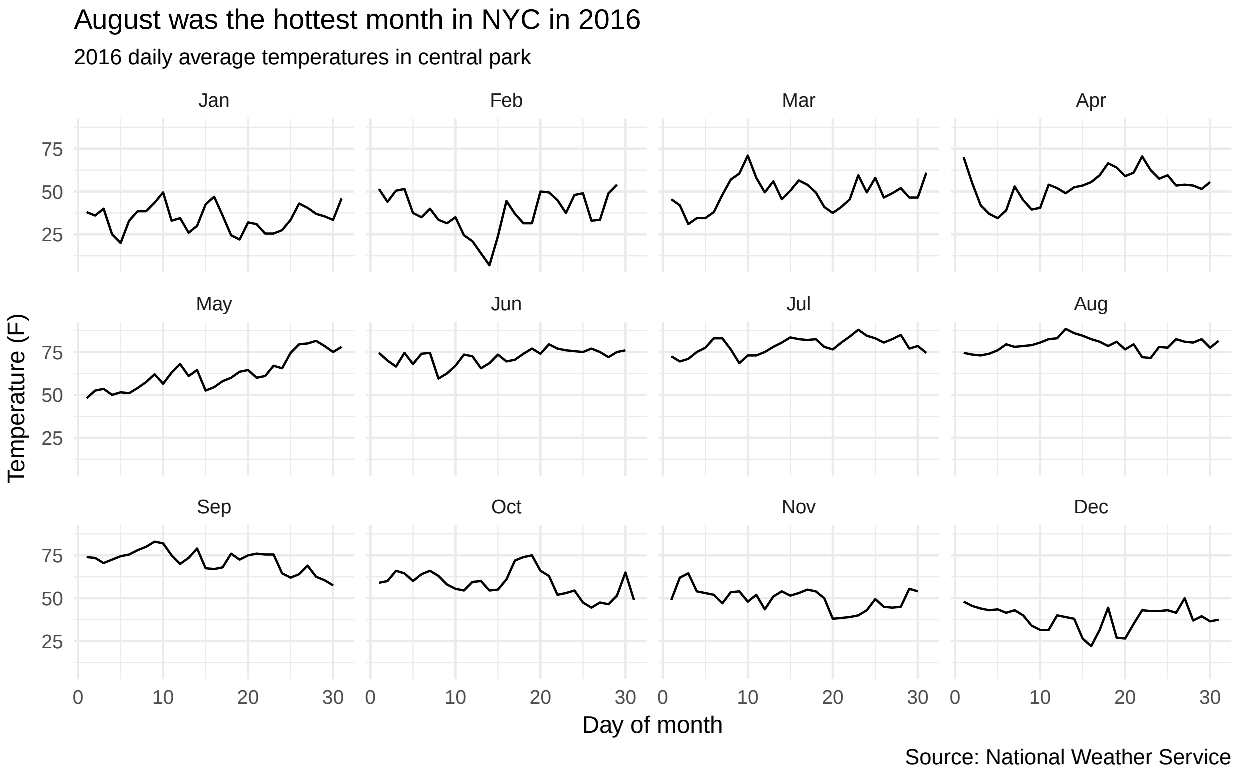
Average temperature in NYC

We did not discuss line plots, but here's an example:

```
p <- ggplot(nyc_long, aes(x = day, y = Temperature)) + geom_line() + facet_wrap(~month)
p
```



Average temperature in NYC



Concluding remarks

- Visualizing your data is important for a multitude of reasons
- It allows you to explore the data and generate insights to help you proceed with later stages of the analysis (e.g. building a predictive model)
- Sometimes, data visualization is a goal on its own, as the case with producing plots for manuscripts or reports
- `ggplot` is a great package to use for data visualizing and it offers a lot more than what was covered in this lesson
- With `ggplot` you can generate publication quality plots for a large variety of geometries (over 30 geoms)